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Driving Consumer Engagement Through AI Chatbot Experience: The Mediating Role of Satisfaction Across Generational Cohorts and Gender in Travel Tourism

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Abstract

This study explores how AI chatbot experiences on travel websites influence consumer engagement, with satisfaction from using AI chatbots as a mediating factor. Grounded in the Stimulus-Organism-Response (S-O-R) framework, the research shifts the focus from utilitarian models to examine how chatbot attributes—e.g., ease of use, information quality, security, anthropomorphism, and omnipresence—affect satisfaction of using AI chatbots and subsequent consumer engagement behaviours. Survey data from 519 Portuguese travellers were analysed using partial least squares structural equation modelling (PLS-SEM). The study contributes to theory by (1) demonstrating S-O-R's advantages over utilitarian models in capturing relational and emotional dimensions of AI interactions, (2) identifying satisfaction with using AI chatbots as a pivotal mediator between AI chatbot experience and consumer engagement, and (3) revealing generational disparities in drivers of engagement. Notably, satisfaction strongly influences engagement for Generation X, while direct experience matters more for Generation Z. Millennials exhibit a distinct preference for hybrid human–AI service handoffs. The practical implications include prioritizing natural language processing for ease of use, implementing generational customization (e.g., gamification for Gen Z, reliability assurances for Gen X), and ensuring seamless human escalation for Millennials. These insights equip travel businesses to design AI chatbots that foster long-term loyalty and competitive differentiation.

Keywords: artificial intelligence; chatbot; consumer engagement; consumer satisfaction; digital innovation; travel website

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1. Introduction

The travel industry has undergone a profound transformation in recent years, driven by the increasing demand for personalized, efficient, and seamless online customer service experiences [1]. E-retailers are compelled to set themselves apart by delivering exceptional customer service and a truly immersive customer experience [2]. As customer expectations increase and competition in the market grows stronger, businesses are employing a range of creative strategies. In this context, the role played by chatbots has developed to increase customer engagement and provide tailored support. This approach has the potential to promote efficiency and also facilitate stronger connections with customers, making their shopping experience more engaging and satisfying than before [3]. As digitalization reshapes consumer expectations, travellers now demand instant, context-aware assistance for booking flights, hotels, and itineraries—preferably across multiple devices and platforms [4]. In response, travel companies are increasingly adopting artificial intelligence (AI)-powered chatbots to deliver 24/7 support, automate bookings, and enhance user satisfaction [5]. These chatbots leverage advancements in natural language processing (NLP) and machine learning to simulate human-like interactions, offering hyper-personalized recommendations and real-time problem resolution [6]. However, despite their potential, chatbot adoption remains uneven, with user acceptance hinging on factors such as ease of use and security [7].

The success of chatbots in travel tourism depends not only on their technical capabilities but also on their ability to foster meaningful consumer engagement—a critical driver of loyalty and repeat purchases [8]. Engagement is particularly vital in the travel sector, where emotional connections and personalized experiences significantly influence decision-making [9]. Prior research has examined chatbot adoption through utilitarian lenses like the Technology Acceptance Model (TAM) [10] or the Unified Theory of Acceptance and Use of Technology (UTAUT) [11], which focus narrowly on functional outcomes such as perceived usefulness. However, these frameworks often overlook the relational and experiential dimensions of human–AI interactions, such as emotional satisfaction or anthropomorphism, which are pivotal in tourism contexts [12].

To address this gap, this study employs the Stimulus-Organism-Response (S-O-R) framework [13,14], which holistically captures how external stimuli (e.g., chatbot design features) trigger internal cognitive and emotional states (e.g., satisfaction), leading to behavioural responses (e.g., engagement) [15]. The S-O-R model is particularly suited to tourism, where personalized, affective experiences drive long-term loyalty [1]. While recent studies have applied S-O-R to AI-mediated services (e.g., [9,12]), few have explored its relevance for travel chatbots, especially in elucidating how satisfaction with the use of an AI chatbot mediates the link between chatbot experience and engagement.

This study aims to bridge these gaps by investigating the following questions: (1) How do chatbot experiences (e.g., ease of use, information quality, anthropomorphism) influence consumer engagement in travel tourism?; (2) What role does satisfaction play in mediating this relationship?; and (3) How do generational and gender factors influence these effects?

This study contributes to the literature on AI-driven consumer engagement in three ways. First, unlike prior work that predominantly applies utilitarian frameworks (e.g., TAM/UTAUT) to chatbot adoption [10,11,16], we employ the S-O-R framework to holistically capture how experiential (e.g., anthropomorphism) and relational (e.g., satisfaction) dimensions shape engagement—as stated above, a critical gap in tourism contexts where emotional resonance drives loyalty [12,17]. Second, we identify satisfaction as a pivotal mediator between chatbot experience and engagement, extending beyond functional metrics to reveal psychological mechanisms underlying sustained usage [3,18]. Third, by uncovering generational asymmetries (e.g., Gen X's reliance on satisfaction vs. Gen Z's focus on direct experience), we challenge the assumption of uniform AI adoption pathways and offer empirically grounded segmentation strategies for chatbots [4]. These contributions collectively shift the discourse from 'whether' chatbots are adopted to 'how' their design evokes differentiated engagement across user profiles.

The remainder of the paper is structured as follows: Section 2 reviews the theoretical background and formulates hypotheses; Section 3 details the methodology; Section 4 presents the results; Section 5 discusses the results and implications; and presents the main conclusions, limitations and future research directions.

2. Theoretical Background and Formulation of Hypotheses

2.1. Recent Advancements in AI Chatbots for Tourism

The rapid growth of AI in the travel industry has led to an increased adoption of chatbots for customer interactions [19,20]. Travel companies, online travel agencies (OTAs), and meta-search engines utilize AI chatbots to deliver real-time customer support, streamline booking processes, and enhance user experience [2–4,21]. Modern chatbots leverage significant advancements in natural language processing (NLP), machine learning, and personalization to deliver context-aware, human-like interactions that go beyond scripted responses [6].

Recent developments in NLP have enabled tourism chatbots to provide hyper-personalized experiences by analysing syntactic structures, user intent, and contextual cues [4]. For instance, modern systems can process colloquial queries such as 'Find me a cosy beachfront villa under $200/night' and dynamically adjust recommendations based on real-time data like weather or local events [22]. Syntactic analysis helps identify nuanced traveller preferences, such as detecting priority keywords like 'family-friendly' or 'luxury', while sentiment analysis adjusts responses to emotional tones, such as suggesting stress-relief activities for frustrated users [9].

Chatbots powered by large language models (LLMs) like GPT-4 [23] utilize deep learning to process natural language with unprecedented contextual awareness. Unlike rule-based predecessors, these systems generate human-like dialogue, adapt to individual preferences through few-shot learning, and integrate multimodal inputs such as text, voice, and image recognition [5]. For example, a chatbot might process a photo of a landmark to provide historical context or navigation assistance [24]. These capabilities address long-standing challenges in tourism, such as delivering hyper-personalized itineraries based on past bookings and real-time requests, managing disruptions like flight cancellations through instant rebooking, and adapting to cultural expectations by detecting linguistic nuances and non-verbal cues [25,26].

However, these technological advancements introduce new considerations for user acceptance. While LLM-powered chatbots improve satisfaction through fluid interactions, their 'black box' decision-making can erode trust if explanations are lacking [27,28]. Similarly, multimodal features risk overwhelming users if not designed intuitively [29]. These challenges underscore the need to revisit traditional adoption frameworks, such as the S-O-R model, to account for AI's evolving role in shaping tourist experiences.

2.2. Theoretical Background

The above-described developments have increased the relevance of studying chatbot adoption and experience in tourism. The literature on technology adoption includes several alternative theoretical frameworks, such as TAM, UTAUT, and the Expectation-Confirmation Theory (ECT), each emphasizing distinct aspects of user behaviour. TAM [10] posits that perceived usefulness and ease of use are primary drivers of technology adoption, focusing narrowly on functional utility. Extending this, UTAUT [11] integrates social influence and facilitating conditions but retains a utilitarian lens. Meanwhile, ECT [30] examines post-adoption behaviour by linking satisfaction to continued use, though it overlooks emotional and environmental stimuli. In contrast, as previously described, the S-O-R framework [13] holistically captures how external stimuli (e.g., chatbot design) trigger cognitive and emotional states (organism), leading to behavioural responses (e.g., engagement). For this study, we elected to use S-O-R because it uniquely accommodates the relational and experiential dimensions of AI chatbot interactions—such as anthropomorphism and emotional satisfaction—which are critical in tourism contexts where personalized, affective experiences drive loyalty [1,12]. While TAM and UTAUT reduce interactions to utilitarian metrics, and ECT neglects initial engagement triggers, S-O-R aligns with the study's goal of dissecting the psychological mechanisms linking chatbot attributes to sustained engagement.

Previous studies have applied the S-O-R model to AI and digital service research, demonstrating that well-designed chatbot experiences improve customer satisfaction and engagement [9,12]. This study extends the application of the S-O-R framework to AI chatbot in travel services, contributing to a deeper understanding of consumer acceptance and engagement mechanisms.

2.3. Formulation of Hypotheses

The aim of this study is to address the research gap by investigating how AI chatbot experience (EXP) affects consumer engagement (ENG), with a focus on the mediating role of satisfaction with the use of AI chatbots (SAT). The S-O-R framework is applied to describe consumer behaviour in chatbot interactions, providing insights into the mechanisms that drive chatbot acceptance and engagement. Despite the efficiency and convenience of chatbots, their acceptance by consumers remains a challenge. Factors such as usability, trust, and perceived intelligence influence whether customers find chatbot interactions satisfactory and engaging [1]. Moreover, customer engagement is a critical aspect of business success in the travel industry, as engaged consumers are more likely to exhibit loyalty, make repeat purchases, and recommend services [8]. As such, our study will focus on the consumer EXP, SAT, and ENG. Furthermore, we will examine the mediating effect of SAT between EXP and ENG.

2.3.1. Chatbot Experience

AI chatbot experience is a critical determinant of user adoption and engagement in digital environments, particularly in the travel and tourism sector. Ease of use (EOU) is foundational to chatbot adoption, as users prefer interfaces that minimize cognitive effort and maximize efficiency [10]. In the context of travel services, where users often seek quick solutions for bookings, inquiries, or itinerary adjustments, a chatbot that is intuitive and effortless to navigate significantly enhances the user experience [31]. Research by Park et al. [32] further supports this, demonstrating that perceived ease of use directly influences customer satisfaction with the use of an AI chatbot by reducing friction in interactions.

Trust (TRS) refers to users' confidence in the reliability, integrity, and security of an AI chatbot's interactions, particularly in handling sensitive data (e.g., payment details, personal information) and delivering accurate, unbiased responses [33,34]. In the context of travel tourism, trust encompasses: competence, that is, the belief that the chatbot can perform tasks accurately (e.g., booking flights, providing real-time updates) [34]; benevolence, which is the perception that the chatbot prioritizes user interests (e.g., offering unbiased recommendations) [33]; and confidence in data protection measures (e.g., encryption, GDPR compliance) [27]. Trust directly enhances satisfaction with the use of AI chatbot by reducing perceived risk and fostering positive emotional evaluations [20]. For instance, users who trust a chatbot's security (e.g., clear privacy policies) report higher satisfaction [35]. In addition, trust also strengthens engagement by encouraging repeat usage (cognitive processing) and emotional attachment (affection) [8]. Kim et al. [34] found that trust in airline e-commerce platforms increased intention to reuse, analogous to chatbot interactions.

Perceived intelligence (PIT) refers to the extent to which users perceive an AI chatbot as capable of understanding, processing, and responding to queries in a competent, knowledgeable, and sensible manner [36]. This construct encompasses attributes such as the chatbot's ability to exhibit responsibility during interactions, provide accurate and contextually relevant responses, and demonstrate problem-solving skills akin to human intelligence [7,36]. PIT is distinct from functional aspects like ease of use or information quality, as it focuses on the user's subjective evaluation of the chatbot's cognitive capabilities. For instance, a chatbot that adapts its responses based on user preferences or handles complex travel-related inquiries (e.g., rebooking flights during disruptions) would likely score high on PIT [6].

Information quality (IFQ) is a cornerstone of effective AI chatbot interactions, particularly in the travel and tourism sector, where accuracy and relevance directly influence decision-making [37]. High-quality information—characterized by timeliness, accuracy, and contextual relevance—ensures that users receive dependable responses to their queries, reducing uncertainty and enhancing confidence in the chatbot's capabilities [22]. For example, a travel chatbot that provides real-time flight updates, precise hotel availability, or personalized destination recommendations significantly improves the user experience by minimizing the need for manual verification [2]. Research by Balakrishnan and Dwivedi [4] emphasizes that chatbots delivering inconsistent or outdated information erode user confidence, leading to disengagement. Moreover, Tussyadiah and Miller [22] highlight that AI-driven responses tailored to user preferences and past behaviours foster positive behavioural changes, such as increased booking intent or higher satisfaction. Thus, superior information quality not only streamlines user interactions but also reinforces the chatbot's role as a reliable travel assistant, ultimately contributing to a more satisfying and engaging experience.

Security (SEC) represents a critical dimension of customer experience in AI chatbot interactions, particularly in the travel and tourism sector, where sensitive personal and financial data are routinely exchanged [36]. Perceived security significantly influences users' willingness to adopt and continue using chatbot services (e.g., [38]). Ashfaq et al. [27] found that security concerns constitute one of the primary barriers to chatbot adoption. The implementation of robust security measures—including end-to-end encryption, multi-factor authentication, and transparent data handling policies—can substantially enhance user trust [29]. Wahbi et al. [35] specifically examined travel industry chatbots and revealed that platforms implementing visible security indicators (e.g., SSL certificates, privacy policy pop-ups) experienced higher satisfaction ratings compared to those without such features. This is particularly relevant for travel chatbots handling hotel bookings, flight purchases, or passport information, where data breaches could have severe consequences. However, security implementation must balance protection with usability. Venkatesh et al. [38] state that excessive security protocols may create friction, potentially undermining the very convenience that makes chatbots appealing. Hasal et al. [29] propose that the most effective solutions employ adaptive security measures that increase rigour proportionally with the sensitivity of requested information; for instance, a travel chatbot might require only basic authentication for itinerary inquiries but implement biometric verification for payment processing. When properly executed, security features become an invisible enabler rather than a barrier—fostering user confidence while maintaining the seamless experience that defines effective chatbot interactions [35]. In the travel sector, where trust is paramount, robust yet discreet security measures can significantly enhance both customer satisfaction and engagement.

Anthropomorphism (ATH)—the attribution of human-like characteristics to chatbots—plays a pivotal role in shaping user perceptions and engagement. Research demonstrates that chatbots designed with human-like traits, such as natural language patterns, emotional expressiveness, or even names and avatars, create more relatable and enjoyable interactions (e.g., [32,39]). In the travel and tourism context, where emotional connection and personalized service are paramount, anthropomorphic chatbots can enhance the user experience by simulating human warmth and understanding [40]. For instance, a chatbot that uses empathetic language ('I understand how frustrating flight delays can be') or humour can alleviate user frustration and foster a sense of connection, mirroring the interpersonal dynamics of traditional customer service [41]. Empirical studies further support that anthropomorphism increases user satisfaction with the use of AI chatbots. Han [39] found that consumers are more likely to make purchase decisions through chatbots perceived as human-like, as they evoke familiarity and reduce scepticism. Similarly, Noor et al. [40] highlight that anthropomorphism recalibrates service quality expectations in AI-driven interactions, making users more forgiving of minor errors when the chatbot exhibits human-like qualities. However, Sfar et al. [41] caution that excessive anthropomorphism can backfire if users perceive the chatbot as disingenuous or uncanny. Thus, striking the right balance is crucial—anthropomorphic elements should enhance, rather than overshadow, the chatbot's functional utility. In travel contexts, where users seek both efficiency and emotional resonance, a well-designed anthropomorphic chatbot can significantly elevate customer experience and drive engagement.

Omnipresence (OMN) refers to the ability of AI chatbots to deliver seamless, cross-platform availability, which has become a fundamental driver of customer experience in travel and tourism [42,43]. This characteristic ensures uninterrupted service accessibility across multiple touchpoints, including mobile apps, websites, social media platforms, and messaging services, allowing travellers to maintain consistent interactions throughout their journey [4]. Research by Reddy et al. [42] demonstrates that omnipresent AI travel companions significantly enhance user satisfaction by reducing friction in cross-channel transitions. The value of OMN is particularly evident in dynamic travel scenarios where real-time assistance is crucial—such as during flight delays, last-minute hotel changes, or emergency situations. Son et al. [43] emphasize that omnichannel integration quality directly influences intention to reuse, as travellers increasingly expect unified experiences whether they interact via smartphone, desktop, or voice assistant. For instance, a chatbot that remembers a user's flight preferences from a web inquiry and subsequently offers boarding pass updates via WhatsApp exemplifies how omnipresence creates convenience and reinforces reliability [42]. However, implementing true omnipresence requires robust backend architecture to synchronize data across channels while maintaining privacy and security standards [4]. When executed effectively, this capability not only meets modern travellers' expectations for always-available service but also positions chatbots as indispensable travel partners, fostering long-term engagement and brand loyalty in an increasingly competitive digital landscape.

Together, the five factors described above—ease of use, information quality, security, anthropomorphism, and omnipresence—create a sound framework for understanding chatbot-mediated customer experience. Their interplay ensures that chatbots not only meet functional needs but also deliver emotionally satisfying and trustworthy interactions, ultimately driving engagement in travel and tourism contexts. A positive chatbot experience is the stimulus (S) in the S-O-R model, influencing user satisfaction with the use of AI chatbots (O) and engagement (R).

2.3.2. Satisfaction with the Use of AI Chatbots

SAT represents a critical psychological response that emerges from positive user evaluations of chatbot interactions. Grounded in the S-O-R framework, satisfaction functions as the organism (O) variable—an internal cognitive and affective state that mediates between chatbot characteristics (stimuli) and subsequent engagement behaviours (responses) [20]. Empirical research demonstrates that satisfaction is essentially shaped by three key dimensions: functional performance (e.g., accuracy, speed), relational quality (e.g., empathy, personalization), and expectation confirmation [2,35]. Satisfied chatbot users exhibit higher repurchase intentions and brand advocacy compared to dissatisfied users [20]. This satisfaction–engagement linkage is particularly strong in travel contexts, impacting repurchase intentions [44]. The dynamic is amplified when chatbots demonstrate adaptive intelligence—the ability to adjust responses based on conversation history and user preferences [2]. For instance, travel chatbots that remember past itinerary preferences and proactively suggest relevant options achieve higher satisfaction scores than generic responders [35]. However, satisfaction thresholds evolve with exposure. As users gain experience with AI interfaces, their expectations for seamlessness and proactivity increase, requiring continuous optimization of chatbot capabilities [44]. This underscores satisfaction's dual role—both as an outcome of current interactions and a baseline for future expectations. When effectively cultivated, SAT becomes a powerful driver of sustained engagement in the travel sector, transforming transactional interactions into relationship-building opportunities.

2.3.3. Consumer Engagement

Consumer engagement (ENG) in the context of AI chatbot-facilitated travel websites represents a multidimensional construct that captures the depth of user involvement and interaction with digital services. Grounded in the S-O-R framework, ENG serves as the critical response (R) variable, reflecting behavioural outcomes driven by chatbot experience (EXP) and SAT [8]. ENG comprises three core dimensions. First, cognitive processing (CPE), that is, the mental effort and attention users devote to chatbot interactions, such as processing travel recommendations or comparing itinerary options [45]. For instance, when chatbots provide personalized destination suggestions that require users to thoughtfully evaluate choices, cognitive engagement intensifies. Second, affection of engagement (AFE), which refers to the emotional connection users develop with the platform, is characterized by feelings of enjoyment, trust, or enthusiasm [45]. A chatbot that uses empathetic language (e.g., 'I've found the perfect beach resort for your anniversary trip!') can evoke positive affective responses. Finally, activation of engagement (ACE), translates into observable behavioural manifestations, including repeated chatbot usage, extended session durations, or sharing travel plans via the platform [9]. For example, users who return to a travel chatbot multiple times to refine their holiday plans demonstrate high activation engagement.

Chatbot experience influences consumer engagement in digital services [46]. In the travel industry, chatbots that deliver seamless, personalized, and informative interactions increase consumer willingness to engage [9]. Zhu et al. [9] found that travellers who rated their chatbot interactions positively (high EXP) exhibited more frequent revisits (ACE) and higher emotional attachment (AFE) to the platform. Similarly, Hollebeek et al. [8] demonstrated that SAT significantly mediates the EXP $\rightarrow$ ENG relationship, as satisfied users are more likely to invest CPE in complex travel planning via chatbots. This follows existing literature showing that satisfaction bridges initial interaction experiences and long-term behavioural outcomes [12]. ENG is not merely an endpoint but a self-reinforcing cycle: highly engaged users provide richer interaction data, enabling chatbots to deliver even more personalized experiences, which further boosts SAT and deepens ENG [9]. High-quality chatbot interactions encourage customers to return to the website, explore services, and make bookings [1]. For travel websites, this virtuous circle translates into increased booking conversions, brand loyalty, and word-of-mouth referrals.

2.3.4. Generational and Gender Differences in Chatbot Engagement

Prior research underscores that generational cohorts and gender groups exhibit distinct psychological and behavioural responses to technology-mediated services [1,9]. Generation

Z (digital natives) tend to prioritize seamless functionality and instant gratification in AI interactions, reflecting their upbringing in hyper-connected environments [4]. In contrast, Generation X are often more risk-averse and place greater emphasis on post-interaction satisfaction as a trust-repair mechanism [25]. Millennials, straddling both analogue and digital worlds, uniquely value hybrid human–AI handoffs, blending efficiency with relational assurance [12].

Gender differences further modulate these effects. Women, on average, exhibit higher sensitivity to relational cues (e.g., anthropomorphism) and emotional satisfaction with chatbot interactions, while men may focus more on utilitarian outcomes like task completion [39,46]. These disparities align with broader sociocultural theories (e.g., [47]) and suggest that the EXP $\rightarrow$ SAT $\rightarrow$ ENG pathways are not uniform across demographics.

2.3.5. Hypotheses and Conceptual Model

Following the literature as described in the previous sections, this study posits that AI chatbot experience influences consumers' satisfaction with using AI chatbots and their engagement, and satisfaction with using AI chatbots mediates the relationship between AI chatbot experience and consumer engagement (mediation effect of satisfaction):

H1. *There is a positive effect of AI chatbot experience on consumer engagement.*

H2. *There is a positive effect of AI chatbot experience on satisfaction with the use of AI chatbot.*

H3. *There is a positive effect of satisfaction with AI chatbot experience on consumer engagement.*

H4. *Satisfaction with using AI chatbots mediates the relationship between chatbot experience and consumer engagement.*

H5. *The relationships between AI chatbot experience, satisfaction with using AI chatbots, and consumer engagement vary significantly across gender groups (H5a) and generational cohorts (H5b).*

The conceptual model is described in Figure 1.

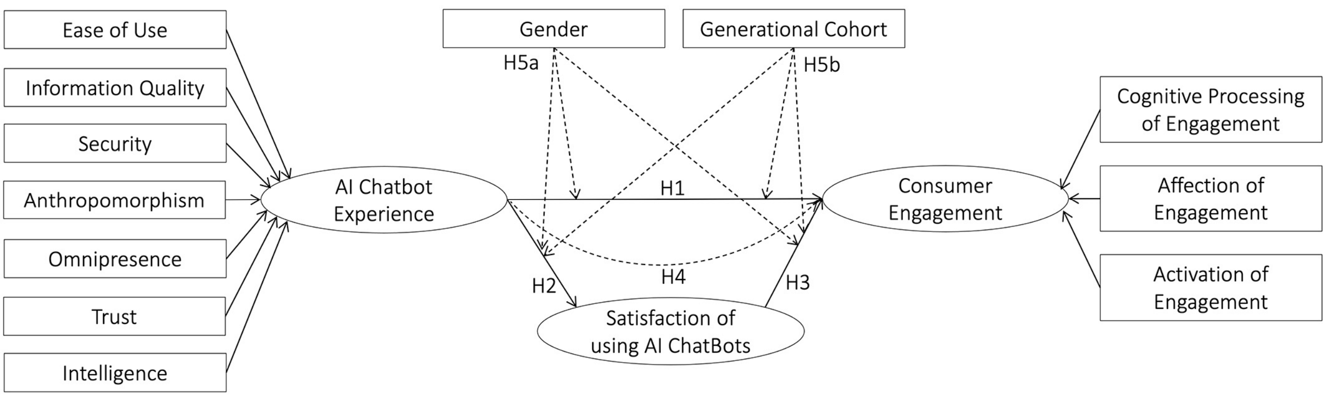

Figure 1. Conceptual model. Note. Relationships are hypothesized to vary by generational cohort and gender (H5); H4 represents the indirect effect between AI chatbot experience and consumer engagement through satisfaction with using AI chatbots.

3. Methods

3.1. Sample Characteristics

The sample consists of 519 respondents, the majority of whom are women, with higher education, and satisfactory income (Table 1). Respondents were categorized into generational cohorts—Generation Z (born 1996–2012), Millennials (1981–1995), Generation X (1965–1980), and Baby boomers (1946–1964)—based on established demographic thresholds [48]. While age is a continuous variable, cohort-based analysis captures shared life experiences (e.g., digital adoption timing, economic climates) that shape technology acceptance [1]. For instance, Generation Z's immersion in mobile-first ecosystems contrasts with Generation X's exposure to later-stage digitalization, justifying cohort-based comparisons over linear age effects [49]. In our sample, the average age is 30.3 years old; most respondents are members of Generation Z.

Table 1. Chatbot experience dimensions.

Variable	Frequency	Percentage
Gender		
Female	312	60.1
Male	207	39.9
Total	519	100.0
Education		
Basic	27	5.2
Secondary/Vocational	168	32.4
Higher education	324	62.4
Total	519	100.0
Income level		
Insufficient	11	2.1
Low	48	9.2
Sufficient	179	34.5
Satisfactory	253	48.7
Higher	28	5.4
Total	519	100.0
Generation		
Generation Z ($\leq$28 years old)	332	64.0
Millennials (29 to 43 years old)	45	8.7
Generation X (44 to 59 years old)	135	26.0
Baby boomers ($\geq$60 years old)	7	1.3
Total	519	100.0
Age	***M*(*SD*)**	**Min–Max**
	30.3 (13.60)	18–90

Notes: *M* = Mean; *SD* = Standard deviation; *Min* = Minimum; *Max* = Maximum.

While geographically focused, Portugal's high digital literacy (85.8% internet penetration in 2023; [50]) and tourism-dependent economy (tourism contributed 21.5% to GDP in 2024; [51]) make it an ideal microcosm for studying chatbot adoption. Portuguese consumers exhibit above-average technology acceptance (ranking 15th in the EU's Digital Economy and Society Index in 2022; [52]), in line with global trends where digitally savvy tourists increasingly prefer AI-driven services [1]. The sample's demographics—predominantly Gen Z (64%) and highly educated (62%)—reflect Portugal's young, urban traveller profile [53] (INE, 2023) and mirror the core user base of travel chatbots worldwide [9]. Though cultural nuances may limit direct generalizability, Portugal's linguistic diversity (20% non-native interactions in tourism; [54]) provides insights applicable to multilingual service contexts. These factors collectively support the sample's relevance for extrapolating patterns in AI-driven tourism engagement.

3.2. Procedures and Instruments

A survey was conducted with a questionnaire that included items drawn from empirical studies. To measure the experience of using AI chatbots on tourism websites, seven constructs were considered. For EOU, four items were adapted from Davis [10], Kim et al. [34], and Oh et al. [31]. For TRS, three items were used from Cyr et al. [55] and Everard and Galletta [56], for PIT five items were used from Bartneck et al. [36] and Balakrishnan and Dwivedi [4], for IFQ, five items were applied from Park et al. [37], for SEC, four items adapted from Noor et al. [40] were used, for ATH, five items were used from Bartneck et al. [36] and Balakrishnan and Dwivedi [4], and for OMN, three items from Baek and Yoo [57]. For SAT, five items were used from Fang et al. [44]. ENG was described by CPE (four items), AFE (four items), and ACE (three items)—all items adapted from Hollebeek et al. [45]. Sociodemographic questions about gender, age, education level, and income were included (see all variables in Table A1 of Appendix A).

The instrument was translated into Portuguese and back-translated into English, according to the guidelines of Streiner et al. [58] and Harkness et al. [59]. The survey was disseminated with LimeSurvey® and included informed consent—each participant in the study was informed in advance about the objectives of the study and the guarantee of anonymity and confidentiality of data, only accessing the questionnaire itself after expressing their consent to accept the terms of participation. Subsequently, a snowball convenience sample comprising adult Portuguese respondents was obtained. A total of 805 answers were obtained between 2 February and 4 April 2025, although only 519 were complete and considered valid. The collected data were processed with SPSS v.29, SPSS AMOS, v.29, and SmartPLS 4.1.0.2.

3.3. Data Analysis

Sociodemographic data and items were characterized with descriptive statistics, namely frequency, percentage, mean, standard deviation, minimum and maximum values, skewness, and kurtosis. The experience in using chatbots scale, composed of six factors, was analysed by determining correlations first, and then whether the absolute values of skewness and kurtosis were below 2.0 and 7.0, respectively [60]. The variance inflation factor (VIF) was calculated [61] to check for multicollinearity (VIF > 10). A principal components analysis (PCA) was conducted with varimax rotation to improve the interpretability of the factorial structure [62].

The measurement instrument was validated using standard psychometric tests. PCA confirmed the expected factor structure (KMO = 0.928; Bartlett's $p < 0.001$) [63,64], with all loadings > 0.7 [61] and communalities above 0.4 [65]. Convergent and discriminant construct validity was analysed using both Fornell and Larcker [66,67] and the heterotrait–monotrait (HTMT) criteria [68]. Confirmatory factor analysis (CFA) demonstrated good fit (CFI = 0.974; RMSEA = 0.049), supporting construct validity (full results are available in the Section 4). Cronbach's α coefficient was calculated to analyse the reliability and internal consistency of the measurement instrument, with good reliability assumed when $\alpha > 0.7$ [69]. Path analysis was carried out for hypotheses testing using partial least squares structural equation modelling (PLS-SEM).

Finally, multigroup analysis was performed to examine differences in path coefficients between groups of gender, generational cohort, and education level in terms of experience with AI chatbot, satisfaction, and consumer engagement. This method is a non-parametric significance test for the difference of group-specific results based on PLS-SEM bootstrapping results. PLS-SEM allows for analysing small subgroups [70]; bootstrapping (5000 samples) ensured the stability of estimates.

As mentioned, we tested our model using PLS-SEM (Figure 2).

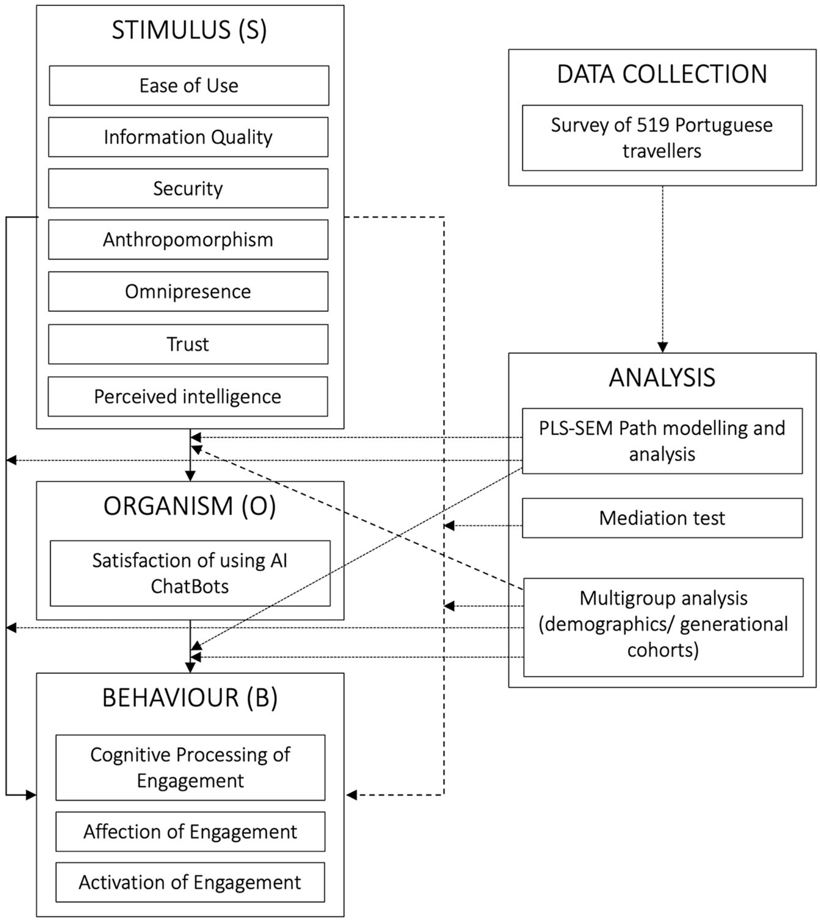

Figure 2. Research model: Linking EXP to ENG via the S-O-R framework and PLS-SEM analysis. Note: Figure 2 depicts the study's theoretical framework (S-O-R) and empirical validation. Solid arrows represent hypothesized relationships, dashed arrows show mediation, and dotted arrows link data to analysis, and the path analysis to the S-O-R paths (validation of theoretical links).

Table 2 highlights PLS-SEM's suitability for testing mediated relationships in small-to-moderate samples.

Table 2. Comparison of analytical methods for AI chatbot research.

Method	Advantages	Disadvantages	Fit for This Study
PLS-SEM	Handles small samples, non-normal data	Lower sensitivity to model misspecification	Aligns with S-O-R's relational focus
CB-SEM	Robust fit indices	Requires large sample size	Unsuitable for $n = 519$
Regression	Simple interpretation	Ignores mediation effects	Cannot test SAT's mediation

4. Results

4.1. AI Chatbot Experience

First, descriptive statistics were determined for EXP items, having found that the correlations among these items were all statistically significant, ranging from 0.104 ($p < 0.05$) to 0.766 ($p < 0.01$), and each item had at least one correlation greater than 0.300. PCA with varimax rotation and Kaiser normalization was used for factor reduction. Instead of seven components, only five were found because all items of trust and perceived intelligence were split into different factors; these items, as well as *iq4*, *iq5*, and *th1*, had factor loadings below 0.7 and were therefore removed. Specifically, TRS items (e.g., 'The AI chatbot is honest and truthful') loaded weakly (λ = 0.42–0.48) on their intended factor, while PIT items (e.g., 'The AI chatbot is competent in providing services') cross-loaded onto anthropomorphism (Δλ > 0.30). This is aligned with prior findings that users struggle to disentangle 'intelligence' from human-like behaviour in conversational AI [7]. As justified ahead, the removal improved model fit and discriminant validity, consistent with scale purification guidelines [69]. While this limits direct measurement of TRS and PIT, their influence is indirectly captured through related constructs (e.g., security for trust; ease of use for competence) [1]. This trade-off prioritizes psychometric rigour while acknowledging the need for refined TRS/PIT measures in future AI studies [25].

Subsequently, the rotated solution organized the remaining items into five factors—EOU, IFQ, SEC, ATH, and OMN, resulting in an 18-factor EXP scale. The Kaiser–Meyer–Olkin measure was excellent (KMO = 0.928), and Bartlett's sphericity test was statistically significant [$\chi^2(153) = 5925.467$, $p < 0.001$], indicating that the data were factorable. All loadings were greater than 0.7, communalities were greater than 0.5, and the scale showed good reliability (Cronbach's $\alpha = 0.928$). Together, the identified components explain 70.3% of the total variance (rotation sums of squared loadings). Convergent and discriminant validity were then assessed. Composite reliability (CR) > 0.7 and average variance extracted (AVE) > 0.5 confirm convergent validity, and the variance shared between the variables does not exceed the square root of the AVE, confirming the discriminant validity (Table 3).

Table 3. AI chatbot experience scale: descriptives, reliability, convergent validity, and discriminant validity.

Variable		*M*	*SD*	Pearson Correlations					Cronbach's α	CR	AVE
				EOU	IFQ	SEC	ANT	OMN			
EOU	Ease of use	3.61	0.724	**0.727**					0.829	0.817	0.528
IFQ	Information quality	3.69	0.724	0.647 **	**0.7649**				0.839	0.809	0.585
SEC	Security	3.17	0.920	0.539 **	0.543 **	**0.7609**			0.902	0.846	0.579
ANT	Anthropomorphism	3.15	1.006	0.476 **	0.482 **	0.712 **	**0.795**		0.898	0.873	0.632
OMN	Omnipresence	3.76	0.763	0.522 **	0.574 **	0.361 **	0.298 **	**0.814**	0.846	0.855	0.663

Notes: *M* = Mean; *SD* = Standard deviation; CR = Composite reliability; AVE = Average variance extracted. Diagonal in **bold**: square root of AVE. ** Correlation is significant at the 0.01 level (2–tailed).

Confirmatory factor analysis was then used to test the instrument that resulted from. A five-factor model was found [$\chi^2(122) = 275.880$, $p < 0.001$], which showed a good fit according to the indicators: NFI = 0.954; TLI = 0.967; CFI = 0.974; RMSEA = 0.049 (0.042–0.057; 90% CI); PCLOSE = 0.543; $\chi^2/df = 2.261$; SRMR = 0.038.

4.2. Satisfaction with the Use of AI Chatbots and Consumer Engagement

PCA was also applied to each remaining scale, namely, satisfaction with the use of AI chatbot, and the consumer engagement subscales of CPE, AFE, and ACE. One item was removed from each consumer engagement subscale due to insufficient loadings (cg4, af4, and ac3). As a consequence, the ACE scale resulted in a three-factor scale with KMO of 0.910, and statistically significant Bartlett's sphericity test [$\chi^2(28) = 2685.927$, $p < 0.001$], with the percentage of total variance explained being 80.5%, and Cronbach's $\alpha = 0.921$. Convergent and discriminant validity are documented in Table 4. CFA was also conducted, showing a good fit [$\chi^2(17) = 51.917$, $p < 0.001$], despite χ^2/df slightly exceeding 3.0: NFI = 0.981; TLI = 0.979; CFI = 0.987; RMSEA = 0.053 (0.034–0.073; 90% CI); PCLOSE = 0.125; $\chi^2/df = 3.054$; SRMR = 0.019.

Finally, the satisfaction scale was examined. The overall KMO was 0.886 and Bartlett's test of sphericity was statistically significant [$\chi^2(10) = 1546.228$, $p < 0.001$]. All items had loadings greater than 0.7 and communalities greater than 0.5, and were organized in a one-factor scale with good reliability (Cronbach's $\alpha = 0.904$).

Table 4. The consumer engagement scale: descriptives, reliability, convergent validity, and discriminant validity.

	Variable	*M*	*SD*	Pearson Correlations			Cronbach's α	CR	AVE
				CPE	AFE	ACE			
CPE	Cognitive processing of engagement	3.47	0.816	**0.778**			0.845	0.822	0.606
AFE	Affection of engagement	3.39	0.881	0.710 **	**0.784**		0.880	0.827	0.614
ACE	Activation of engagement	3.38	0.947	0.667 **	0.723 **	**0.807**	0.834	0.788	0.651

Notes: *M* = Mean; *SD* = Standard deviation; CR = Composite reliability; AVE = Average variance extracted. Diagonal in **bold**: square root of AVE. ** Correlation is significant at the 0.01 level (2–tailed).

4.3. Item Characterization

Table 5 documents all items used in the study, indicating loadings, commonalities, mean, standard deviation, skewness, kurtosis, and variance inflation factor. All parameters fell within cut-off values for loadings, commonalities, skewness, and kurtosis. There was no evidence of multicollinearity (the highest VIF value was 2.988).

Table 5. Variables and item characterization.

Variable	λ	h^2	*M*	*SD*	*Sk*	*Kr*	*VIF*
EOU			3.61	0.724	−0.157	0.396	
eu1	0.717	0.587	3.54	0.941	−0.403	0.182	1.527
eu2	0.781	0.765	3.65	0.843	−0.350	0.418	2.270
eu3	0.658	0.645	3.59	0.896	−0.479	0.364	1.814
eu4	0.745	0.696	3.65	0.878	−0.414	0.217	2.043
IFQ			3.69	0.724	−0.360	0.754	
iq1	0.775	0.749	3.62	0.894	−0.475	0.421	1.869
iq2	0.763	0.773	3.75	0.877	−0.464	0.242	2.072
iq3	0.757	0.752	3.75	0.861	−0.576	0.646	2.020
SEC			3.17	0.920	−0.331	0.677	
sc1	0.781	0.754	3.14	1.015	−0.270	−0.222	2.146
sc2	0.764	0.788	3.08	1.065	−0.050	−0.537	2.710
sc3	0.763	0.797	3.20	1.062	−0.218	−0.390	2.988
sc4	0.736	0.780	3.27	1.043	−0.241	−0.354	2.869
ANT			3.15	1.006	−0.210	−0.131	
th2	0.813	0.778	3.12	1.152	−0.250	−0.728	2.542
th3	0.840	0.813	3.07	1.236	−0.223	−0.859	2.891
th4	0.775	0.779	3.14	1.117	−0.246	−0.602	2.775
th5	0.749	0.728	3.29	1.090	−0.301	−0.407	2.124
OMN			3.76	0.763	−0.287	−0.517	
mn1	0.790	0.748	3.69	0.925	−0.516	0.219	1.956
mn2	0.854	0.810	3.82	0.839	−0.480	0.352	2.223
mn3	0.798	0.756	3.77	0.849	−0.378	0.059	2.026
SAT			3.64	0.788	−0.306	0.393	
st1	0.843	0.710	3.58	0.910	−0.272	−0.106	2.324
st2	0.869	0.755	3.61	0.958	−0.392	−0.024	2.663
st3	0.830	0.690	3.62	0.914	−0.285	−0.036	2.183
st4	0.856	0.732	3.74	0.940	−0.482	−0.064	2.503
st5	0.850	0.723	3.67	0.912	−0.461	0.250	2.438
CPE			3.47	0.816	−0.323	0.453	
cg1	0.817	0.789	3.51	0.928	−0.404	0.243	2.016
cg2	0.781	0.788	3.45	0.937	−0.342	0.084	2.223
cg3	0.735	0.739	3.46	0.935	−0.292	0.052	1.917
AFE			3.39	0.881	−0.374	0.253	
af1	0.774	3.43	0.99	−0.378	−0.047	0.421	2.343
af2	0.794	3.35	0.99	−0.298	−0.094	0.242	2.377
af3	0.782	3.39	0.96	−0.281	−0.081	0.646	2.629
ACE			3.38	0.947	−0.457	0.018	
ae1	0.821	0.859	3.32	1.040	−0.355	−0.252	2.047
ae2	0.792	0.847	3.44	1.004	−0.458	−0.078	2.047

Notes: λ = Loadings; h^2 = Communalities; *M* = Mean; *SD* = Standard deviation; *Sk* = Skewness, *Kr* = Kurtosis; VIF = Variance inflation factor. EOU = Ease of use; IFQ = Information quality; SEC = Security; ANT = Anthropomorphism; OMN = Omnipresence; SAT = Satisfaction with using AI chatbots; CPE = Cognitive processing of engagement: AFE = Affection of engagement. ACE = Activation of engagement.

4.4. Model Reliability, Internal and External Validity

The structural equation model was adjusted to include the variables displayed in Table 5 and run using PLS-SEM in SmartPLS 4. Two second-order variables were created: EXP, comprising EOU, IFQ, SEC, ANT, and OMN, and consumer engagement (ENG), including CPE, AFE, and ACE. Table 6 documents the correlations between each variable of the model, namely, Cronbach's α, CR, and AVE. Reliability is very good (all Cronbach's α values are greater than 0.8). All AVE are above the minimum recommended value of 0.5 [67], ranging from 0.666 (EOU) to 0.858 (ACE). CR values are above the recommended minimum of 0.6 [67], ranging from 0.835 (ACE) to 0.906 (SEC), which indicates that all the constructs have adequate internal consistency. Discriminant validity was measured using two criteria: the Fornell–Larcker and HTMT. The results, displayed in Table 6, allow us to conclude that the variables have discriminant validity, as all the correlations between them are lower than the square root of the AVE (diagonal in bold), while the HTMT values are below 0.9.

Table 6. Reliability and discriminant validity.

	EOU	IFQ	SEC	ANT	OMN	SAT	CPE	AFE	ACE
EOU	**0.816**	*0.740*	*0.623*	*0.554*	*0.623*	*0.738*	*0.671*	*0.602*	*0.574*
IFQ	0.620	**0.870**	*0.568*	*0.489*	*0.662*	*0.776*	*0.660*	*0.676*	*0.599*
SEC	0.543	0.494	**0.879**	*0.791*	*0.412*	*0.650*	*0.708*	*0.678*	*0.651*
ANT	0.484	0.427	0.713	**0.875**	*0.343*	*0.618*	*0.683*	*0.673*	*0.709*
OMN	0.526	0.560	0.361	0.306	**0.875**	*0.788*	*0.548*	*0.524*	*0.408*
SAT	0.642	0.676	0.587	0.559	0.692	**0.850**	*0.781*	*0.737*	*0.680*
CPE	0.565	0.555	0.618	0.597	0.464	0.683	**0.874**	*0.823*	*0.794*
AFE	0.518	0.581	0.604	0.600	0.454	0.657	0.710	**0.898**	*0.844*
ACE	0.480	0.500	0.566	0.615	0.344	0.591	0.668	0.724	**0.926**
Cronbach's α	0.834	0.880	0.898	0.921	0.845	0.928	0.839	0.848	0.904
CR	0.923	0.926	0.929	0.936	0.907	0.937	0.903	0.908	0.928
AVE	0.858	0.806	0.766	0.645	0.764	0.454	0.757	0.766	0.722

Notes: Diagonal elements are the square roots of the AVE (average variance extracted). HTMT values are presented in italics above the diagonal elements. The correlations between the constructs are shown below the diagonal elements. EOU = Ease of use; IFQ = Information quality; SEC = Security; ANT = Anthropomorphism; OMN = Omnipresence; SAT = Satisfaction with using AI chatbots; CPE = Cognitive processing of engagement; AFE = Affection of engagement; ACE = Activation of engagement. Cronbach's α based on only two items.

4.5. Testing of Hypotheses

A path analysis was performed on the structural model, considering the sign, magnitude, and statistical significance of the parameters of the analysed relationships, a procedure aligned with Götz et al. [67]. All the constructs were measured at a 5% statistical significance level. Moreover, the coefficient of determination (R^2) was determined for the endogenous variables—SAT (R^2 = 0.635) and ENG (R^2 = 0.642). The evaluation of the hypotheses employed linear regression coefficients utilizing PLS-SEM. Table 7 shows the outcomes (direct, specific, and total effects).

Table 7. Estimated direct, indirect, and total effects.

Path	β	CILL (0.025)	CIUL (0.0925)	t	p	f^2	Hypotheses Decision	
Direct effects								
EXP → ENG	0.569	0.469	0.670	11.017	0.000	0.330	H1	Supported
EXP → SAT	0.797	0.754	0.832	40.451	0.000	1.743	H2	Supported
SAT → ENG	0.270	0.145	0.381	4.513	0.000	0.074	H3	Supported
Specific effects								
EXP → SAT → ENG	0.215	0.216	0.001	4.427	0.000	Partial mediation	H4	Supported
Total effects	0.784	0.742	0.819	39.932	0.000			

Notes: β = Estimates; CILL = Confidence interval lower limit with corrected bias; CIUL = confidence interval upper limit with corrected bias; f^2 = Effect size. EOU = Ease of use; IFQ = Information quality; SEC = Security; ANT = Anthropomorphism; OMN = Omnipresence; SAT = Satisfaction with using AI chatbots; CPE = Cognitive processing of engagement; AFE = Affection of engagement; ACE = Activation of engagement.

All structural relationships examined show positive signs and parameters, in line with the assumptions articulated in the literature review (Figure 3). Furthermore, the direct effect of EXP on ENG (β = 0.569, $p < 0.001$) is greater than the indirect effect (β = 0.215, $p < 0.001$). That strong direct effect underscores its pivotal role in tourism service design. For context, this coefficient suggests that a one-unit increase in positive chatbot experience corresponds to a 56.9% improvement in engagement behaviours—an effect size exceeding thresholds for substantive impact in behavioural research [71]. Practically, this implies that optimizing chatbot interfaces (e.g., improving ease of use or anthropomorphism) could increase repeat website visits. To complement this analysis and gauge the strength of the mediation effect of satisfaction with the use of AI chatbot, the three-factor approach proposed by [72] was employed, which allows us to examine how the indirect effect complements the direct effect. In this case, satisfaction is positive (complementary effect) and partially mediates the mentioned relationship.

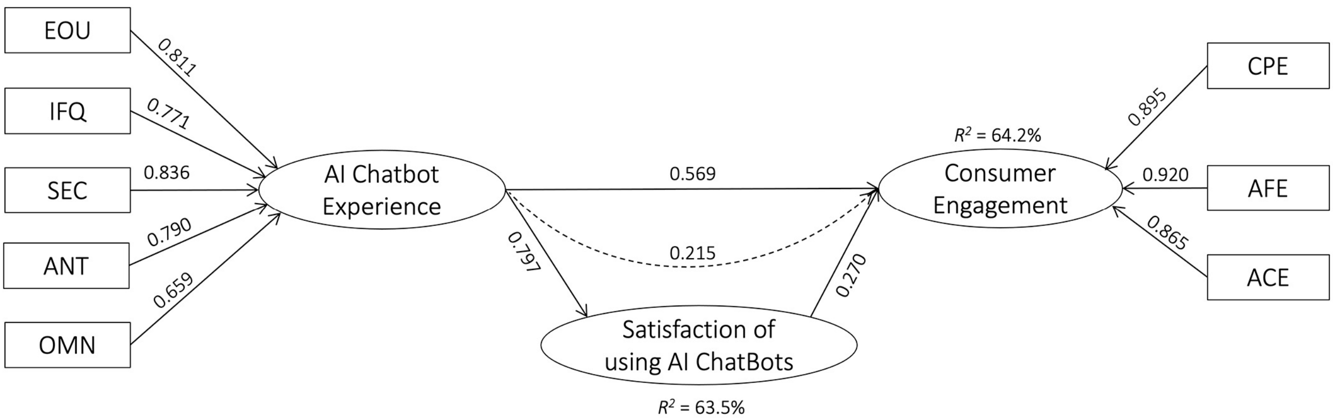

Figure 3. PLS-SEM results.

The partial mediation by satisfaction further reveals that while experience drives immediate engagement, satisfaction amplifies long-term loyalty—a critical insight for allocating resources between initial usability improvements (e.g., NLP accuracy) versus relational features (e.g., emotional intelligence training for AI) [7]. These findings are aligned with meta-analytic evidence that AI service quality impacts retention more strongly in tourism than other sectors, highlighting chatbots' strategic value for competitive differentiation [73,74].

4.6. Multigroup Analysis

In this subsection, we look at notable variations between gender, generational cohorts, and education level groups in terms of EXP, SAT, and ENG by running a multigroup analysis (PLS–MGA). Table 8 compares the results obtained for women and men and shows that all relationships between EXP and SAT and ENG, as well as between SAT and ENG, are statistically significant. However, there are no significant differences between the two groups in these relationships at the 5% significance level.

Table 8. Multigroup comparison—females vs. males.

Paths	**Females**		**Males**		**Females—Males**	
	β	***p***	**β**	***p***	**β Coef. diff.**	***p***
Direct effects						
EXP → EN	0.525	0.000	0.638	0.000	−0.113	0.139
EXP → SAT	0.796	0.000	0.797	0.000	−0.001	0.488
SAT → ENG	0.295	0.000	0.225	0.013	0.070	0.291

Table 8. *Cont.*

Paths	Females		Males		Females—Males	
	β	*p*	β	*p*	β Coef. diff.	*p*
Indirect effects						
EXP → SAT → ENG	0.208	0.000	0.179	0.014	0.050	0.301
Total effects						
EXP → ENG	0.760	0.000	0.817	0.000	−0.057	0.071

Notes: β = Estimate coefficient; *p*—*p*-value; Coef. diff. = Coefficient differences; EXP = AI chatbot experience; SAT = Satisfaction with using AI chatbots; ENG = Consumer engagement.

To compare the influence of age, Table 9 documents the multigroup analysis conducted by generational cohort—Gen. Z, Gen. Y (Millennials), and Gen. X (the oldest group, Baby boomers, was not included in this analysis because the respective number of cases was too small). In this case, the path estimators are statistically significant for all cohorts. However, there is a statistically significant difference in the direct effect as the relationship between the EXP and SAT is stronger for Gen. Y than for Gen. Z (β_{diff} = −0.130, *p* = 0.015) and Gen X (β_{diff} = 0.098, *p* = 0. 047). The direct relationship between the EXP and ENG is statistically significantly stronger in Gen. Z than in Gen. X (β_{diff} = 0.215, *p* = 0.032) and, in contrast, lower concerning the relationship between SAT and ENG (β_{diff} = −0.241, *p* = 0.036). The indirect relationship between the EXP and ENG is also statistically significantly stronger in Gen. Z than in Gen. X (β_{diff} = −0.197, *p* = 0.031). These results may suggest that for older consumers, engagement is more strongly influenced by satisfaction (because of the experience with AI chatbot) than it is for young people. For Millennials, the path coefficients revealed that the impact of EXP was stronger than for their counterparts.

Table 9. Multigroup comparison—generational cohorts.

Paths	Gen. Z		Gen. Y		Gen. X	
	β	*p*	β	*p*	β	*p*
Direct effects						
EXP → ENG	0.628	0.000	0.621	0.000	0.413	0.000
EXP → SAT	0.760	0.000	0.890	0.000	0.792	0.000
SAT → ENG	0.194	0.005	0.313	0.027	0.435	0.000
Indirect effects						
EXP → SAT → ENG	0.147	0.006	0.278	0.029	0.344	0.000
Total effects						
EXP → ENG	0.775	0.000	0.900	0.000	0.758	0.000
Paths	**Gen Z—Gen Y**		**Gen Z—Gen X**		**Gen Y—Gen X**	
	β coef. diff.	*p*	**β coef. diff.**	*p*	**β coef. diff.**	*p*
Direct effects						
EXP → ENG	0.007	0.488	0.215	0.032	0.208	0.128
EXP → SAT	−0.130	0.015	−0.032	0.237	0.098	0.047
SAT → ENG	−0.119	0.245	−0.241	0.036	−0.122	0.260
Indirect effects						
EXP → SAT → ENG	−0.131	0.192	−0.197	0.031	−0.066	0.340
Total effects						
EXP → ENG	−0.124	0.002	0.018	0.367	0.142	0.003

Notes: β = Estimate coefficient; *p*—*p*-value; Coef. diff. = Coefficient differences; EXP = AI chatbot experience; SAT = Satisfaction with using AI chatbots; ENG = Consumer engagement.

At this point, it is important to note that while generational comparisons revealed significant differences, the uneven sample sizes (e.g., Gen Z: *n* = 332; Millennials: *n* = 45) warrant caution. Small subsamples (e.g., baby boomers: *n* = 7) limit statistical power and generalizability for underrepresented groups [71]. However, the robustness of PLS-SEM for small group sizes [70] and the alignment of findings with prior cohort studies (e.g., Gen Z's preference for direct experience) [9] support the validity of the detected patterns. Future research should oversample smaller cohorts (e.g., Millennials, baby boomers) to validate these trends.

Finally, to complete the structural relationships analysis, an MGA was carried out by education level (Table 10). Although no differences in path coefficients between education level groups are statistically significant, all direct, indirect, and total effects are statistically significant within the higher education level consumers. For basic and secondary-level consumers, the direct relationship between SAT and ENG is not statistically significant, nor the specific indirect path between EXP and ENG.

Table 10. Multigroup comparison—education level.

Paths	**Basic Education**		**Secondary Education**		**Higher Education**	
	β	***p***	**β**	***p***	**β**	***p***
Direct effects						
EXP → ENG	0.560	0.013	0.620	0.000	0.533	0.000
EXP → SAT	0.777	0.000	0.790	0.000	0.804	0.000
SAT → ENG	0.382	0.070	0.202	0.055	0.303	0.000
Indirect effects						
EXP → SAT → ENG	0.297	0.064	0.160	0.059	0.244	0.000
Total effects						
EXP → ENG	0.857	0.000	0.780	0.000	0.777	0.000
Paths	**Basic—Secondary**		**Basic—Higher**		**Secondary—Higher**	
	β coef. diff.	***p***	**β coef. diff.**	***p***	**β coef. diff.**	***p***
Direct effects						
EXP → ENG	−0.060	0.372	0.027	0.475	−0.087	0.222
EXP → SAT	−0.013	0.494	−0.028	0.441	0.014	0.369
SAT → ENG	0.180	0.260	0.078	0.342	0.101	0.244
Indirect effects						
EXP → SAT → ENG	0.137	0.249	0.053	0.337	0.084	0.236
Total effects						
EXP → ENG	0.077	0.188	0.080	0.171	−0.003	0.458

Notes. β = Estimate coefficient; *p*—*p*-value; Coef. diff. = Coefficient differences; EXP = AI chatbot experience; SAT = Satisfaction with using AI chatbots; ENG = Consumer engagement.

5. Discussion

This study examined the acceptance and use of AI-powered chatbots on travel websites, focusing on how chatbot experiences and user satisfaction shape consumer engagement. The results are aligned with prior research while offering new insights into the relational and experiential dimensions of human–AI interactions in the travel industry (e.g., [12,32,35]).

The study confirmed that AI chatbot experience—comprising ease of use, information quality, security, anthropomorphism, and omnipresence—significantly influences consumer engagement (H1: $\beta = 0.569$, $p < 0.001$). This finding is aligned with the S-O-R framework, which posits that external stimuli (chatbot attributes) trigger internal cognitive and emotional states (satisfaction), leading to behavioural responses (engagement) [13]. The strong direct effect of chatbot experience on engagement underscores the importance of designing intuitive, secure, and human-like chatbots to foster user interaction. This extends prior work by [1], who emphasize the role of perceived usefulness and ease of use in AI adoption but do not explore their cumulative impact on engagement.

Grounded in the S-O-R framework, the findings highlight the mediating role of satisfaction with using AI chatbots in the relationship between chatbot experience and consumer engagement. SAT emerged as a critical mediator (H4: $\beta = 0.2159$, $p < 0.001$), partially explaining the relationship between chatbot experience and engagement. This supports Huang and Rust's [12] assertion that satisfaction bridges functional and emotional evaluations of AI services.

While satisfaction partially mediates the EXP $\rightarrow$ ENG relationship, this mechanism is not uniform across all users as the multigroup analysis provides robust support for H5, confirming that the relationships between EXP, SAT, and ENG vary significantly across generational cohorts and gender groups. As such, the analysis shows that SAT is more influential for older generations (Gen X: $\beta_{SAT \rightarrow ENG} = 0.435$, $p < 0.001$), than for younger users (Gen Z: $\beta_{SAT \rightarrow ENG} = 0.194$, $p = 0.005$). This generational divergence suggests that older consumers prioritize reliability and post-interaction evaluations, while younger users focus on immediate experiential aspects [9]. These findings enrich the S-O-R model by demonstrating how demographic factors moderate psychological responses to AI stimuli.

If SAT strongly predicts engagement for Generation X ($\beta_{SAT \rightarrow ENG} = 0.435$, $p < 0.001$), suggesting chatbots should prioritize reliability (e.g., accurate bookings, crisis support) over novel features, in contrast, Generation Z ($\beta_{EXP \rightarrow ENG} = 0.628$, $p < 0.001$) responds most to direct experience, favouring visually interactive interfaces (e.g., AR previews, meme-infused dialogues) that are aligned with their digital-native expectations [9]. Moreover, Millennials uniquely value hybrid human–AI handoffs ($\beta_{EXP \rightarrow SAT} = 0.890$, $p < 0.001$), indicating a need for seamless escalation to live agents during complex requests. These results complement recent work by Balakrishnan and Dwivedi [74], who highlighted the role of personalization in chatbot acceptance but did not explore generational variations, and lead us to recommend error-proofing with clear recovery protocols (e.g., automated rebooking guarantees) for the Gen X segment, gamified reward systems for engagement (e.g., loyalty points for chatbot usage) for the Gen Z segment and enable seamless transitions to human agents for complex queries (e.g., group trip planning) for Millennials.

It is possible to derive various practical implications from our insights, in addition to generational customization. First, travel companies and chatbot developers should prioritize design, specifically optimizing ease of use and information quality, as these were the most influential dimensions of the chatbot experience. For example, integrating natural language processing (NLP) to improve response accuracy [6] and ensuring omnipresence across devices can enhance user satisfaction. Then, they should address the 'black box' perception of AI by providing explanations for chatbot decisions, critical for fostering trust, especially among older users.

This study provides new insights into the factors that influence the acceptance and use of chatbots on travel websites, highlighting how these technologies can enhance tourist decision-making, service efficiency, and the personalization of travel experiences. By examining the relationships between consumer experience, satisfaction, and engagement, and incorporating generational differences and psychological mechanisms that underlie chatbot adoption, this study contributes to the growing field of AI-driven customer service in the travel sector.

This study also confirms that satisfying experiences with travel chatbots leads to increased consumer engagement with the service. For the tourism sector, this reinforces the importance of investing in easy-to-use, secure chatbots that provide high-quality information and exhibit human characteristics. The accuracy, relevance, and completeness of responses, as well as data protection and accessibility on different devices, are key factors in improving the experience. The results contain important information for travel companies, chatbot developers and marketers. Understanding the factors influencing the acceptance of chatbots can help optimize the design and implementation of these tools, increasing customer satisfaction, promoting engagement, and building long-term relationships with consumers. Thus, this study underscores the dual role of EXP and SAT in driving consumer engagement, with generational nuances calling for tailored design strategies. By integrating S-O-R theory with contemporary AI literature, the study provides a framework for optimizing chatbot interactions in tourism—balancing functionality, emotional resonance, and demographic adaptability—and offers a relational perspective on engagement, complementing functional adoption theories, and providing actionable insights for generational customization. As AI continues reshaping travel services, these insights offer a roadmap for enhancing customer loyalty and competitive differentiation.

However, some limitations should be highlighted. The fact that the study was carried out exclusively in Portugal may restrict the generalisability of the results to other cultural and geographical contexts. Additionally, the sample may not adequately represent all users of travel websites, as it did not account for potential differences between users with varying levels of familiarity with this technology, which could influence their experience and perception of chatbots. Also, the cross-sectional nature of the study design precludes causal inferences; longitudinal studies could track how chatbot interactions evolve over time [45]. The limited representation of Millennials (n = 45) and baby boomers (n = 7) precludes definitive conclusions for these groups, suggesting future replication with balanced samples.

As noted in Section 4.1, TRS and PIT items were removed due to weak loadings and cross-loadings, but this trade-off between statistical and theoretical rigour warrants caution in interpreting engagement drivers. This decision introduces a tension between our theoretical framework and empirical results. Prior research underscores that TRS and PIT are foundational to AI adoption in high-risk contexts like travel bookings [27,36], and their absence may limit the model's ability to fully capture risk-related hesitations. However, we note that these dimensions are indirectly reflected in retained constructs: security (SEC) proxies for transactional TRS, while ease of use (EOU) and anthropomorphism (ATH) collectively approximate PIT through usability and human-like adaptability [7]. Future studies should refine these constructs—perhaps by distinguishing between competence-based and benevolence-based trust [33]—or employ mixed methods to reconcile quantitative metrics with qualitative insights on user scepticism.

Concerning future research, the proposals to be considered involve conducting studies in different countries and cultures to validate the generalizability of the results. Also, carrying out qualitative studies through interviews or focus groups should be considered, to gain a deeper understanding of users' experiences with chatbots and to assess the influence of digital literacy and familiarity with technology on acceptance and satisfaction with chatbots. Longitudinal studies should also be carried out to analyse the evolution of acceptance and use of chatbots over time. This study demonstrates that chatbot experience and satisfaction are critical drivers of consumer engagement in travel tourism. By applying the S-O-R framework, it provides a holistic view of how AI-mediated interactions influence user behaviour. The findings underscore the need for tailored chatbot designs that cater to generational preferences and prioritize transparency. As AI continues to transform the travel industry, these insights offer a roadmap for enhancing customer loyalty and competitive advantage.

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Appendix A

Table A1. Variables.

	Item	Author(s)
EXP	AI chatbot experience	
EOU	Ease of use	
eu1	The AI chatbot for tourism requires little mental effort to plan travel.	Davis (1989) [10]
eu2	It is easy to use an AI chatbot for tourism for my travel plan and booking.	Kim et al. (2009) [34]
eu3	My interaction with the AI chatbot for tourism is clear and understandable for planning my tours.	Oh et al. (2013) [31]
eu4	The AI chatbot for tourism is simple to use for travel planning and booking.	
IFQ	Information quality	
iq1	The content of the AI chatbot's response is well founded.	Park et al. (2007) [37]
iq2	The content of the AI chatbot's response is objective.	
iq3	The content of the AI chatbot's response is understandable.	
SEC	Security	
sc1	There is no risk of loss associated with disclosing personal information to the AI chatbot.	Noor et al. (2022) [40]
sc2	I feel secure in providing sensitive information to the AI chatbot.	
sc3	I believe the information that the AI chatbot has about me is protected.	
sc4	I trust that my personal information with the AI chatbot will not be misused.	
ANT	Anthropomorphism	
th1	The AI chatbot is natural; it does not feel fake.	Bartneck et al. (2009) [36]
th2	The AI chatbot is more humanlike.	
th3	The AI chatbot is conscious of its actions.	
th4	The AI chatbot feels lifelike and not artificial.	Balakrishnan and Dwivedi (2024) [4]
th5	The AI chatbot is elegant in engaging.	
OMN	Omnipresence	
mn1	I can contact this AI chatbot anywhere.	Baek and Yoo (2018) [57]
mn2	I can use the AI chatbot on multiple devices.	
mn3	Using the AI chatbot will not be limited by place.	
TRS	Trust	
tr1	The AI chatbot is honest and truthful.	Cyr, D., Head, M., Larios, H. and Pan, B. (2009) [55]
tr2	The AI chatbot is capable of addressing my issues.	
tr3	The AI chatbot's behaviour and response meet my expectations.	Everard, A. and Galletta, D.F. (2005) [56]
PIT	Perceived intelligence	
it1	The AI chatbot is competent in providing services.	Bartneck et al. (2009) [36]
it2	The AI chatbot is knowledgeable during service interactions.	
it3	The AI chatbot exhibits responsibility during service interactions.	Balakrishnan and Dwivedi (2024) [4]
it4	The AI chatbot has intelligent functions concerned with services.	
it5	The AI chatbot is sensible during service replies.	
SAT	Satisfaction with using the AI chatbot	
st1	Overall, I feel extremely satisfied with this AI chatbot.	Fang et al. (2014) [44]
st2	Overall, I feel extremely pleased with this AI chatbot.	
st3	My expectations of this AI chatbot are achieved.	
st4	I would recommend this AI chatbot to a friend.	
st5	Overall, the quality of the AI chatbot's response is high.	
ENG	Consumer engagement	
CPE	Cognitive processing of engagement	
cg1	Using this tourism site gets me thinking about this OTA site.	Hollebeek et al. (2014) [45]
cg2	I think about this OTA site a lot when I'm using it.	
cg3	This OTA site is one of the brands I usually use when I use tourism sites.	
cg4	The OTAs with an AI chatbot are the ones I usually use when planning my trips.	
AFE	Affection of engagement	
af1	I feel very positive when I use this OTA site.	Hollebeek et al. (2014) [45]
af2	Using this OTA site makes me happy.	
af3	I feel good when I use this OTA site.	
af4	I'm proud to use this OTA site.	

Table A1. *Cont.*

	Item	Author(s)
ACE	Activation of engagement	
ae1	I spend a lot of time using this OTA site, compared to other tourism sites.	Hollebeek et al. (2014) [45]
ae2	Whenever I'm using OTA sites, I usually use this site.	
ae3	Using this OTA site stimulates my interest in learning more about this tourism site.	
	Demographic variables	
gender	Female (0), Male (1)	Own source.
age	Metric	
educ	Education level: Basic (0), Secondary/Vocational (1), Higher education (2)	
income	Insufficient (1), Low (2), Sufficient (3), Satisfactory (4), High (5)	
gener	Generation: Generation Z (0; ≤28 years old), Millennials (1; 29 to 43 years old), Generation X (2; 44 to 59 years old), Baby boomers (3; ≥60 years old)	

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